A Comprehensive Trading Strategy Model for Forecasting and Scheme-Planning

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Abstract. Due to the complexity and variability of the financial market, the current model can not fully cover all aspects of investment trends, and there is room for improvement in forecasting accuracy and decision-making. Based on this, we propose a CNN-LSTM prediction method combining RMSE loss, and use DDPG algorithm based on Actor-Critic framework to make decision. This method innovatively combines RMSE loss functions of two models. In order to prove the rationality of this model, we choose several models to compare with it, and finally come to the conclusion that our model has a good feasibility and universality in prediction and decision-making.

Keywords: CNN · LSTM · Actor-Critic · DDPG · Mean semi-variance model

1 Introduction

Gold refers to a kind of precious metal, relatively rare and precious. Ornaments made of it are not only beautiful but also regarded as a symbol of one's wealth, so they are often bought by people. At the same time, gold has a certain monetary function, in some countries and enterprises, has served as a special bitcoin for reserves and investment.

Bitcoin is a digital currency that, unlike most other currencies, is not issued by a specific bitcoin institution but is generated by a specific algorithm based on a large number of calculations. It is accepted and invested by more and more people because of its limited total volume, decentralized issuance and trading, and transparent trading records.

And in gold and bitcoin investment, there must be some risk. Some people invested heavily in gold and bitcoin, reaping big profits. Some people were out of their savings because of greed. Therefore, the price prediction and investment research of gold and Bitcoin have always been concerned by people.

2 Our Work

In order to get the maximum profit, we set up two models to solve this problem; They are prediction model and decision model.

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For the Model I: Through the observation of data and searching for relevant materials, we found that the price of gold and bitcoin had complex nonlinear and unstable characteristics when predicting the price of gold and bitcoin. Therefore, we choose CNN neural network to predict the price in the part with big fluctuation. LSTM model was used to forecast the whole. Furthermore, we combine both models based on the principle of minimal RMSE. At the same time, due to the instability of the price, it is not possible to predict the data for a long time, so we have added an automatic update mechanism. When the predicted value is significantly different from the actual value, we will re-train the model to obtain more accurate prediction results.

For the Model II: When making decisions, we choose the more advanced Actor-Critic framework for reinforcement learning through the interaction between Policy network and Value network to make the best judgment, and DDPG algorithm is used to accelerate convergence. In checking to see the superiority of this model, we compare this model with the commonly used Mean-semi-variance model, and measure the benefits and risks of this model through cumulative wealth and Max-Dawn-down. To illustrate the superiority of our decision model. Finally, we adjust commissions to observe the sensitivity of the strategy to transaction costs.

3 Prediction Model

3.1 LSTM Prediction Model

LSTM model is suitable for extracting time series features from time series, has the ability to learn long-term time series dependency relationship, and has good prediction effect, and is widely used for the prediction of time series [5]. The price change of gold and bitcoin is a typical time series. Therefore, we first predict the price of gold and bitcoin based on the LSTM model.

For the three thresholds of LSTM, namely, the input gate, the forgetting gate and the output gate, we adopt the most common structure as shown in Fig. 1.

The specific steps for establishing LSTM are as follows:

Step 1: Forget gate settings:

$$F_k = f[W_f \cdot [h_{k-1}, x_{k-1}] + \theta_f] \tag{1}$$

Step 2: Input status update:

$$\begin{cases} I_k = f[W_n \cdot [h_{k-1}, x_{k-1}] + \theta_n] \\ S_k = g[W_n \cdot [h_{k-1}, x_{k-1}] + \theta_s] \end{cases}, \tag{2}$$

Step 3: Update the neural network state:

$$S_k = f_k \cdot S_{k-1} + I_k \cdot \widetilde{S}_k, \tag{3}$$

Step 4: Network output:

$$\begin{cases} O_k = f\left[W_o \cdot \left[h_{k-1}, x_{k-1}\right] + \theta_o\right], \\ \widetilde{S}_k = O_k \cdot g(S_k). \end{cases} \tag{4}$$

After the processing of g(·) in step 4, the value in the interval $[-1, 1]$ will be obtained, and by multiplying with O_k, the neural network output will be finally obtained.

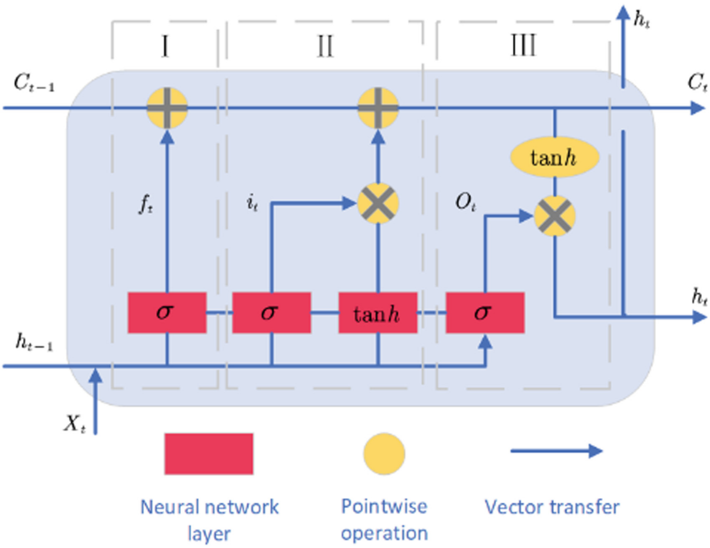


Fig. 1. The network cell structure of LSTM

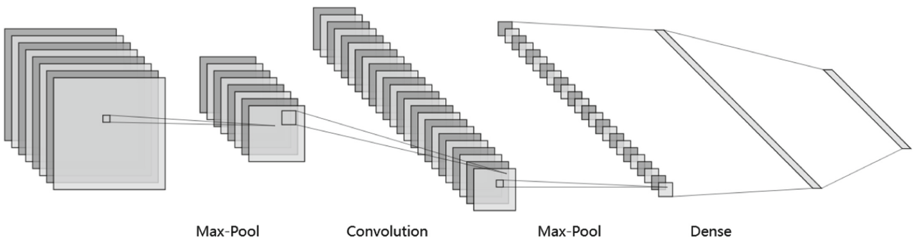
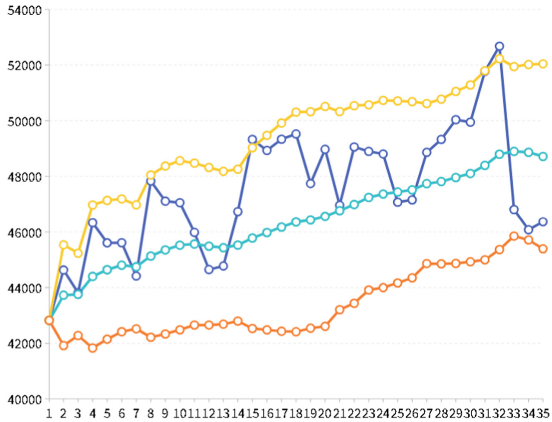


Fig. 2. The network cell structures of CNN

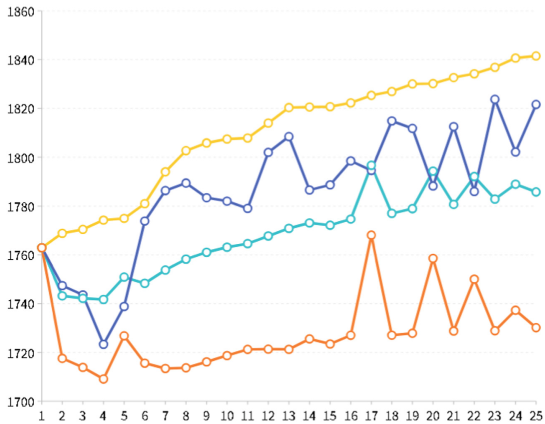
3.2 CNN Prediction Model

CNN is a feedforward neural network with meaningful structure and convolution computation [3], which can extract hidden features from data and combine them layer by layer to generate abstract high-level features. It is often used in image recognition and speech recognition, and has achieved great success and basic structure is shown in Fig. 4. We hope to predict the price of gold coins and bitcoin by identifying the curve of the price and time of gold coins and bitcoin (Fig. 2).

In the input layer, we introduce the Bollinger Bands. Bollinger Band is part of the commonly used tools for stock market technical analysis. It can predict the market by obtaining the standard deviation of stock price and then calculating the trust interval of stock price. The price trend of gold and bitcoin is similar to that of stock price, so we introduce The Brin index to help CNN predict the price of gold and bitcoin.



a)Bollinger Bands of gold in a month



(b)Bollinger Bands of bitcoin in a month

Fig. 3. CNN's input figures.

Where the Bollinger Band involves the calculation of middle rail (MB), upper rail (UP) and lower rail (DN). Let's take bitcoin as an example and calculate the Daily Bollinger Bands,

$$MB_{bitcoin} = MA, \tag{5}$$

$$UP_{bitcoin} = MB_{bitcoin} + 2MD, \tag{6}$$

$$DN_{bitcoin} = MB_{bitcoin} - 2MD. \tag{7}$$

The final input layer is shown in Fig. 3.

In the convolution layer, we carry out the convolution operation on the input to extract the deep features of the data. The process of convolution is expressed as:

$$C = f(X \otimes W + b), \tag{8}$$

Where C is the output characteristic graph of the convolution layer, X is the input data and the price curve established by us in the input layer; f(.) is the nonlinear activation function, ⊗ is the convolution operation, W is the weight vector of the convolution kernel, and b is the bias term [4].

In the pooling layer, we use certain pooling rules to pool the output of the convolution layer, which can be regarded as an equivalent process of dimensionality reduction to retain the main features and reduce the number of parameters and computation to prevent over-fitting.

Finally, input of the full connection layer to obtain the desired output results through calculation. Here, we will only output the predicted price of gold and bitcoin.

3.3 Two-Dimensional Price Prediction Model of Combined RMSE

When predicting the price of gold and bitcoin, we train the time series data and the price curve at the same time, and complement the two models to get the price prediction result. Here, we refer to the existing literature and fuse LSTM and CNN models based on the premise of minimum RMSE. For the prediction model, there are:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{R}_i - R_i)^2}, \tag{9}$$

Where X is the predicted value and Y is the true value. RMSE is an important indicator to reveal relatively large prediction errors. Here, we fuse the two models based on the principle of minimum total RMSE, and RMSE calculation is shown as follows:

$$Total\ \ RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\beta\hat{R}_i^{LSTM} + \gamma\hat{R}_i^{CNN} - PC_{gold(i)})}, \tag{10}$$

Where X and Y are the predicted values obtained by using LSTM or CNN models. β and γ are expressed as the RMSE weight of LSTM and CNN for the total RMSE. Our goal is tantamount to minimize total RMSE. For β and γ, we use Bisection method [6], where the values of β and γ are not fixed, as we will describe below.

3.4 A Self-updating Mechanism for the Model

Through observation of data and understanding of relevant background knowledge, we find that the prices of gold and bitcoin are affected by many factors and have complex instability, nonlinear and periodic instability. Therefore, it is obviously unrealistic to achieve long-term prediction of gold and bitcoin prices. We established a self-updating mechanism for the model.

Specifically, we use the past data to ensure that a long-term prediction of future data. Then, at the end of the week, we calculated the performance index of R^2 for the past week to assess. Where, the larger R^2, the closer to 1, the better the fitting effect of the model is. Here we define updating the model when R^2 is below 0.85 for the past week.

3.5 Predicted Results of the Model

We use the data of gold price and bitcoin price from September 10th, 2016 to September 11th, 2021.

First of all, in order to test the validity of the model, we selected the data of the first 300 days of gold for testing. The first 100 days are the training set. The final prediction results of LSTM are shown in Fig. 4.

By comparing the predicted value with the real value, we find that the predicted result of LSTM is better, and the overall trend is close to the real trend. However, there are some shortcomings. Some local trends change too small, too gentle. CNN's prediction results are shown in the Fig. 5.

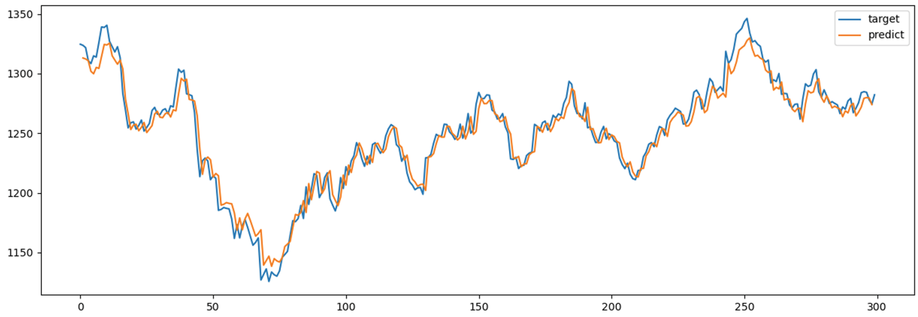


Fig. 4. The predicted and target values of the LSTM model

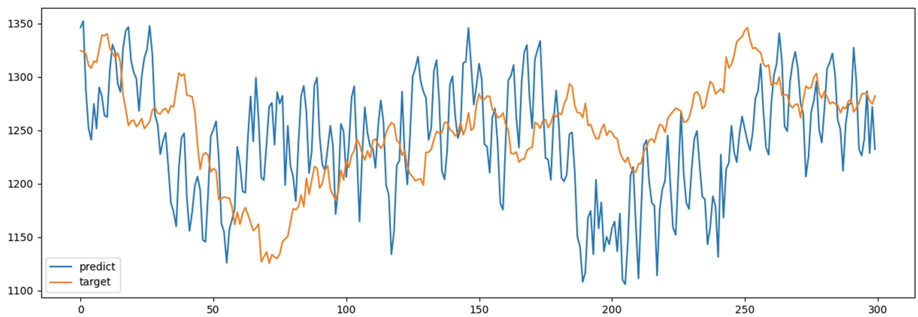


Fig. 5. The predicted and target values of the CNN model

By comparing the predicted value with the real value, we find that the overall trend of the CNN model is poor, but the local performance is outstanding, which can reflect some subtle local changes. It shows that CNN model is more suitable for predicting the rise and fall of prices. The prediction results after the fusion of the two models are shown in the Fig. 6.

It can be seen from the Fig. 6 that after the combination of the two models, the overall prediction effect has been significantly improved. We calculated RMSE of these three models respectively as shown in the Table 1 (Figs. 7 and 8).

Since our time window is 5 weeks, meaning we can't use historical data to predict future prices on any day of the first 5 weeks, we don't invest in the first 5 weeks, which we call a wait-and-see period.

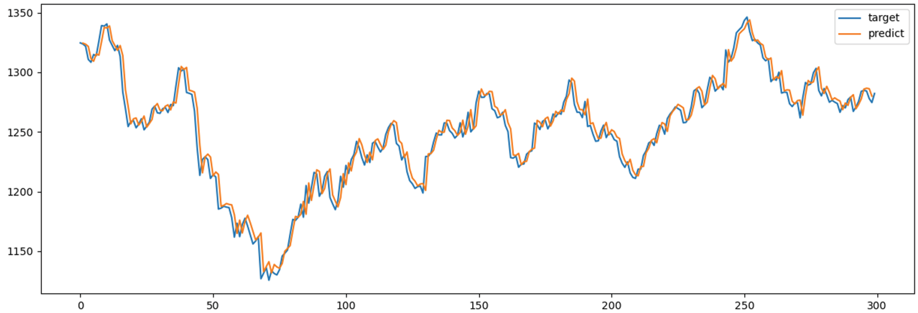


Fig. 6. The predicted and target values of the Two-dimensional Model of Combined RMSE

Table 1. RMSE for different models.

	LSTM	CNN	CNN-LSTM
RMSE	11.0	66.93	9.54

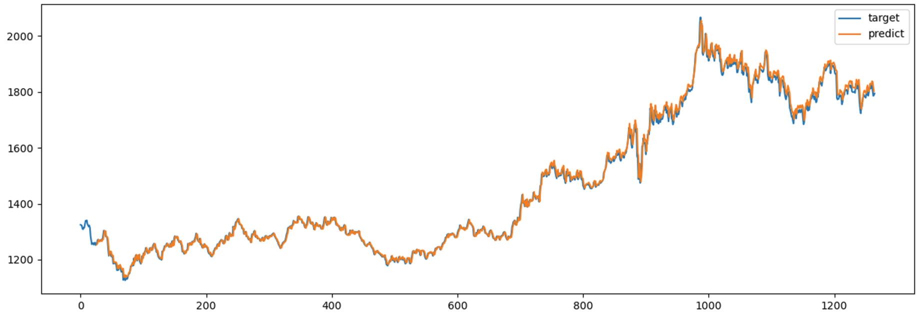


Fig. 7. The predicted and target values of gold

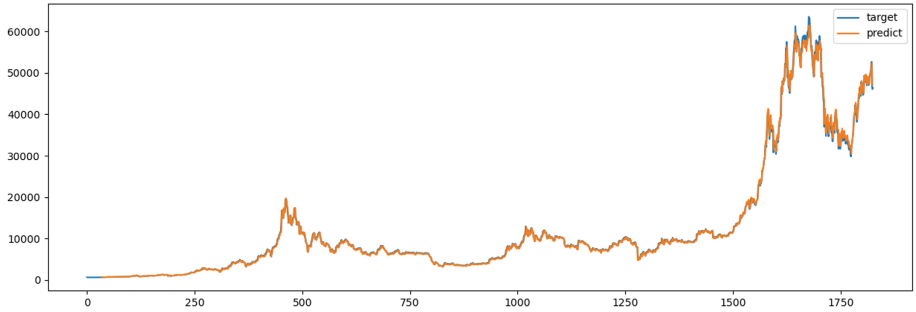


Fig. 8. The predicted and target values of bitcoin

4 Decision-Making Model

4.1 Investment Strategy Decision Model Based on Actor-Critic Framework

4.1.1 The Basic Framework of Actor-Critic

Each day traders hold different amounts of money, gold and Bitcoin. Traders need to make a buying and selling strategy based on the predicted price of gold and bitcoin in the near future to maximize profits by buying and selling gold and bitcoin. For this typical decision problem, we will build a decision model based on Actor-Critic Framework to solve it.

The Actor-Critic framework is divided into Actor and Critic. When trading, Actor is the trader, and the main choice of action is to buy and sell gold and bitcoin. The daily holding of gold, bitcoin and money is the input State of Actor. Maximizing the wealth held by the trader is the purpose of the Actor part. As for the Critic separate, it mainly evaluates the changes in value caused by the actions of the trader and points out whether the trader realizes the value or not. And the trader will adjust his strategy according to the Critic's evaluation and make a better performance in the resulting decision.

4.1.2 Introduction of DDPG Algorithm

Since ordinary Actor-Critic algorithm is difficult to converge, some other optimizations are needed. Therefore, DDPG algorithm is introduced to accelerate the convergence of Actor-Critic framework.

DDPG has four networks. Actor-online network is responsible for iterating the policy network parameter θ, and selecting the current action. According to the current state S, which is used to generate $S'\ ^{R}$with the environment. $\text{Actor}_{\text{target}}$ network is responsible for selecting the optimal next action A′ based on the next state S′ sampled in the empirical replay pool. $\text{Critic}_{\text{online}}$ network is responsible for the iterative update of the value network parameter w, responsible for calculating the current Q value Q(S, A, W). $\text{Critic}_{\text{target}}$ network is in charge of calculating the $Q'(S', A', W')$ part of the target Q value.

The structure of DDPG algorithm is shown in the Fig. 9.

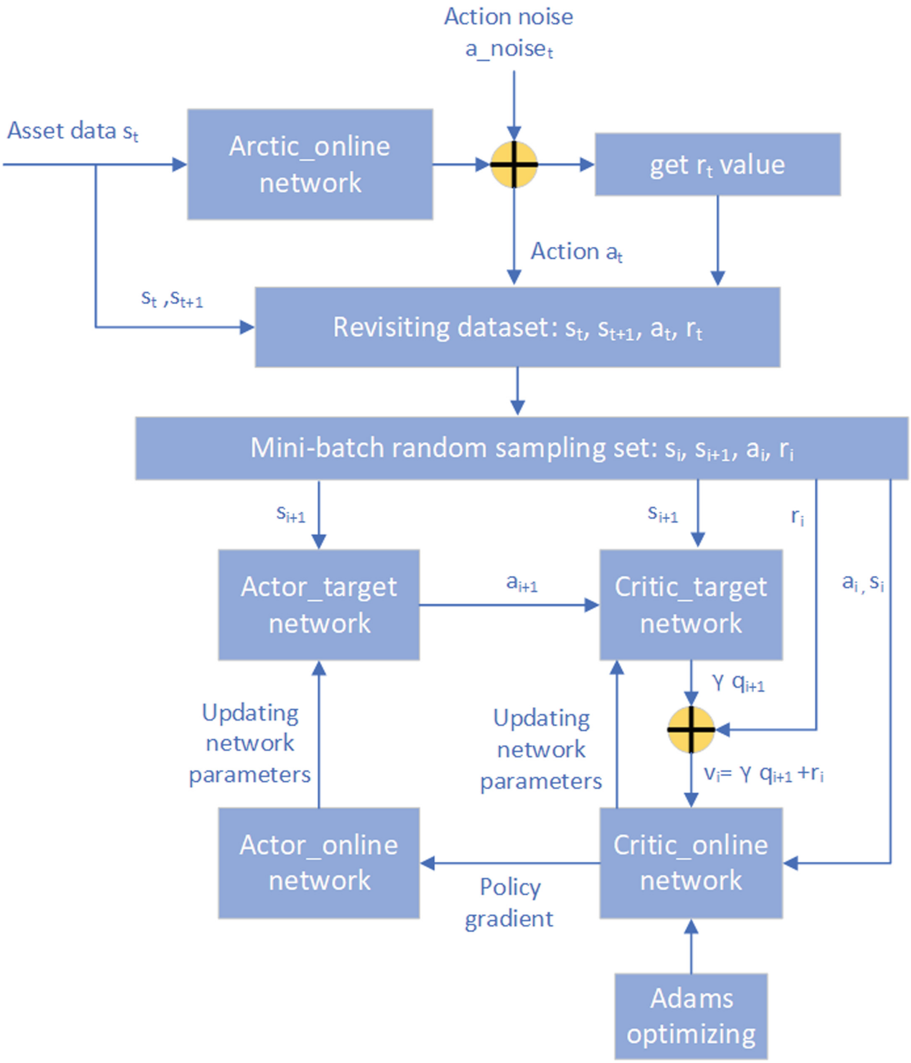


Fig. 9. The structure of DDPG algorithm

4.1.3 Investment Strategy and Results

The final purchase strategy is shown in the Figs. 10 and 11.

Where, up means buying signal, and down means selling signal. As the first five weeks for a wait-and-see period, do not buy and sell. The real buying and selling begin after the first buying occurs. After being the optimal strategy, the trader ends up with $377551.74 in assets. The accumulation of assets is shown in Fig. 12.

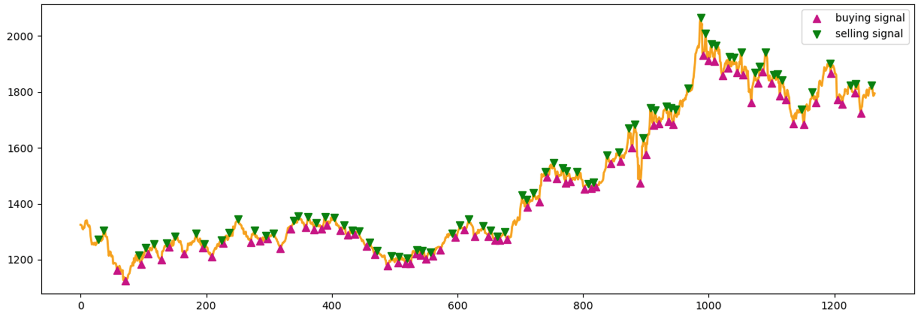


Fig. 10. Buy or sell signal chart for gold

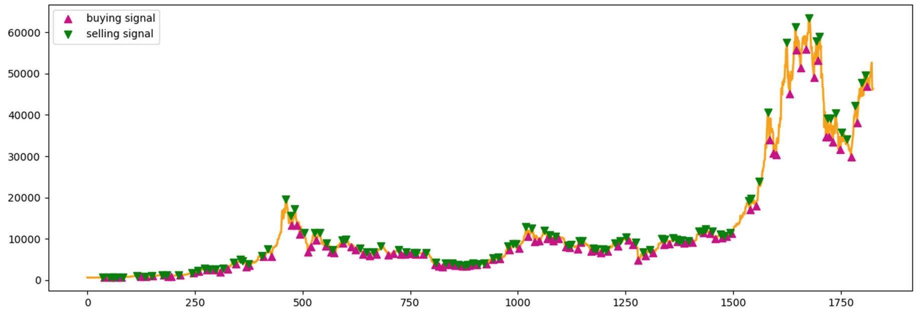


Fig. 11. Buy or sell signal chart for bitcoin

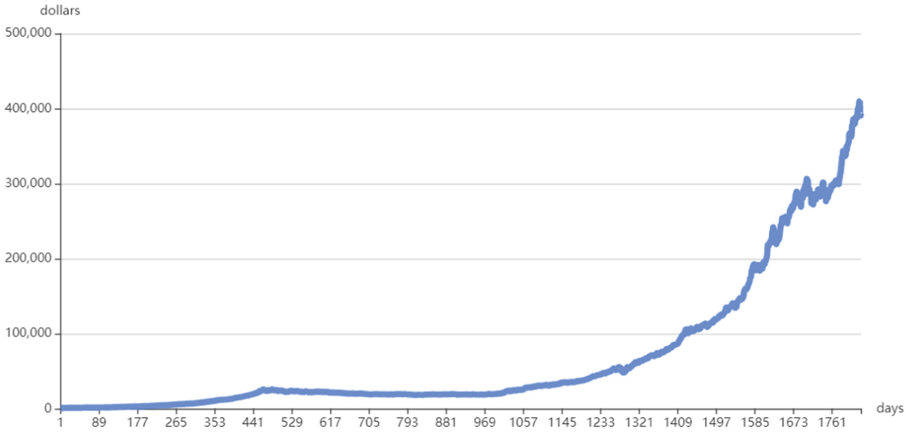


Fig. 12. Assets accumulation map

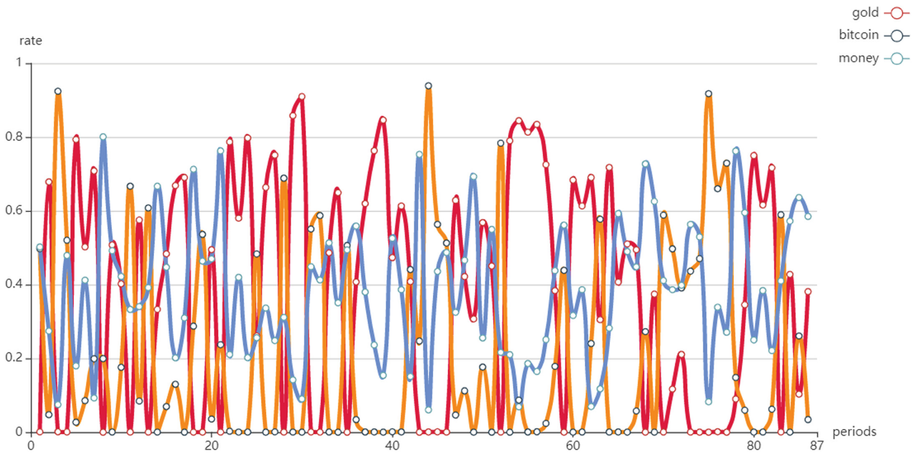


Fig. 13. The decision results of The Mean semi-variance model

4.2 Mean Semi-variance Model

In order to verify that the strategy made by the model is the best strategy, we use the traditional Mean semi-variance model to calculate the investment results and compare the results with the decision model based on actor-Critic framework.

Its core is how to determine the strategy, so that the risk of the portfolio is not greater than the maximum risk investors bear, the maximum possible return. Mean-variance model is an improvement of mean-variance model, which is mainly reflected in the definition of risk. Mean-variance model often defines risk as the uncertainty of returns. However, the Mean-semivariance model [1] takes into account that in actual investment, traders tend to interpret risk as loss, that is, when the return rate of investment is higher than the expected return rate, it is not considered as a risk, but when the actual return rate is lower than the expected return rate, it is considered as a risk. Therefore, we use the Mean semi-variance model to develop a practical trading strategy.

As the Mean Semi-variance Model is a very classic model, the detailed steps are not described in detail in this paper, and only the related results are given in Fig. 13.

Then, there is only one transaction in each period, that is, at the beginning of the period, the buyer buys gold and Bitcoin according to the purchase ratio given by the model. After investing in accordance with this strategy, the trader will eventually obtain $315118.30 of assets.

5 Model Comparison

It can be seen from the final assets that the decision model based on Actor-Critic framework performs better. However, in order to further verify that the strategy obtained by our model is the best strategy, we select accumulated wealth and MaxDawndown as indicators for non-parametric test.

Taking the cumulative wealth index as an example, the ranking is conducted according to the test results of the two models' investment in gold and bitcoin. The higher the accumulated wealth, the smaller the ranking value. The setting value of the I dataset in the $j_{algorithm}$ is represented as r_{ji}. Sort and assign. Calculate the average sequence value of the algorithm in each data set according to the order value obtained.

Based on the principle that the performance of the two models is the same under the Friedman test of the row, the statistics are:

$$\chi F = \frac{12N}{k(k+1)}[\sum R_j^2 - \frac{k(k+1)^2}{4}], \tag{11}$$

It follows a k – 1 Chi-square distribution with degrees of freedom. After improvement by Iman and Davenport, the statistics changed to:

$$F_F = \frac{(N-1)\chi F^2}{N(k-1) - \chi F^2}, \tag{12}$$

The statistics obey the F distribution with degrees of freedom of K – 1 and (K – 1)(n – 1). Where N is the number of data sets, that is, 2, and k is the number of models, the calculated value of F_F is 167.2, which is larger than the critical value of 161.44 at the significance level of F(1, 1) $\alpha = 0.05$. Therefore, the assumption that the performance of the two algorithms is the same ones is rejected. In the actual results, the decision model based on Actor-Critic Framework is more profitable and its performance is better.

At the same time we also with MaxDawndown was carried out by the statistical test, the MaxDawndown [2] refers to the selected cycle push back any historical moment, the net value of products in low yield maximum retracement amplitude, is the important indicators of risk investment, finally also concludes that the decision-making model based on the Actor – Critic framework has a better performance.

6 Conclusions

In order to solve the optimal investment problem, this paper establishes a prediction model and a decision model respectively, in which the prediction model has significantly improved the prediction accuracy compared with the traditional LSTM model, and the decision model adopts the Actor-Critic deep learning framework of DDPG algorithm, which has significantly improved the yield and risk compared with the traditional mean-semivariance model. The combination of the two models can solve the investment decision-making problem intelligently.

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